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Prepared by:

Boston Fusion Corp.

1 Van de Graaff Drive, Suite 107

Burlington, MA 01803

Submitted to:

Jeffrey Morrison, Code: 341

Office of Naval Research

875 North Randolph St.

Arlington, VA 22203-1995

jeffrey.g.morrison@navy.mil

Technical Point of Contact:

Thomas G. Allen

Office: 617-583-5730 x109

Mobile: 978-317-0326

Fax: 617-583-5730

tom.allen@bostonfusion.com

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14. ABSTRACT This report documents the progress made under the Info-Cognitive Proactive Decision Support (InfoCog) project of the Proactive and Adaptive Decision Support Study (PDS) program. InfoCog, to be developed by the team of Boston Fusion Corp. and Aptima, Inc. combines two different perspectives essential for proactive decision support: a data-centered representation of the mission information space (Boston Fusion) and a user-centered representation of the human decision space (Aptima). InfoCog will overcome the limitations and drawbacks of today's Decision Support Systems that adopt only the information or human decision spaces.						
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1 INTRODUCTION

This report documents the progress made under the *Proactive and Adaptive Decision Support Study* (PDS) project. The PDS project team is led by Boston Fusion Corp., with Aptima, Inc. as the sole teammate (subcontractor). The period of performance (PoP) of the reported effort is 28 July 2014 to 31 December 2014. This customer for this program is the Office of Naval Research (ONR), with Jeffrey Morrison, Ph.D., as the ONR technical representative.

2 OVERVIEW OF INFO-COGNITIVE PROACTIVE DECISION SUPPORT (INFOCOG)

2.1 INTRODUCTION

Today's commanders must adapt decision making tasking and priorities in response to uncertain, dynamic, and sometimes urgent operational environments. Commanders and their staff need to wade through a seemingly ever-increasing sea of data to identify the key information need to make important decisions. Automating this process is non-trivial due to the wide range of operating conditions and uncertainty. The goal of the Office of Naval Research *Proactive Decision Support* (PDS) program is to “invest in basic and applied research that aims to mitigate the challenges faced by today's decision makers” ultimately to develop a “Science of Context-Driven Decision Making (CDDM)” and practical PDS tools.

Effective decision support should enhance a decision maker's ability to explore data and promptly apply the appropriate tools. To be truly effective, decision support must operate within the proper context view, satisfying potentially complex task demands, in support of an overall mission. By developing context awareness of decision makers' missions and tasks, a PDS system should anticipate decision and information needs, and use that awareness to pre-compute and pre-position the information to support those decisions. In the context of “Information Support,” we have identified key operational and technical challenges, which are listed in Table 2-1.

Table 2-1. Operational and related technical challenges of PDS Information Support.

Operational Challenges	Technical Challenges
Operate under uncertain and evolving requirements, environments, and user states	Understand the operational context and recognize changes
Know what additional information or resources are required to improve understanding and or decision quality	Estimate value of information and resources in context
Make decisions in a timely manner	Rapidly pre-position resources so that the right information is available as the situation unfolds

In response to these challenges, the team of Boston Fusion and Aptima will develop a system design, create and evaluate component algorithms, and implement a proof-of-concept demonstration for an integrated system called *Info-Cognitive Proactive Decision Support* (InfoCog). InfoCog combines two different perspectives essential for proactive decision support: a data-centered representation of the mission information space (Boston Fusion) and a user-centered representation of the human decision space (Aptima). InfoCog will overcome the limitations and drawbacks of today's Decision Support Systems (DSSs) that adopt only the information or human decision spaces. By blending both techniques, InfoCog will generate and deliver better formatted, more relevant, and more timely information products to tactical operators.

InfoCog, structured around three core layers of processing (Figure 2-1), will:

1. Model and estimate current mission states, and hypothesize future mission states to identify the likely future relevance of mission information (*Information Layer*).
2. Capture user interactions to infer current and future task needs, and user states to anticipate how current and likely decision processes need to be supported through information delivery (*Cognition Layer*).
3. Provide anticipatory decision support through the delivery of formatted, relevant and timely information products, derived from a thorough and dynamic understanding of mission states and operator's related information needs, and use that understanding to process and present system results without requiring the user to request them explicitly (*Decision Support Layer*).

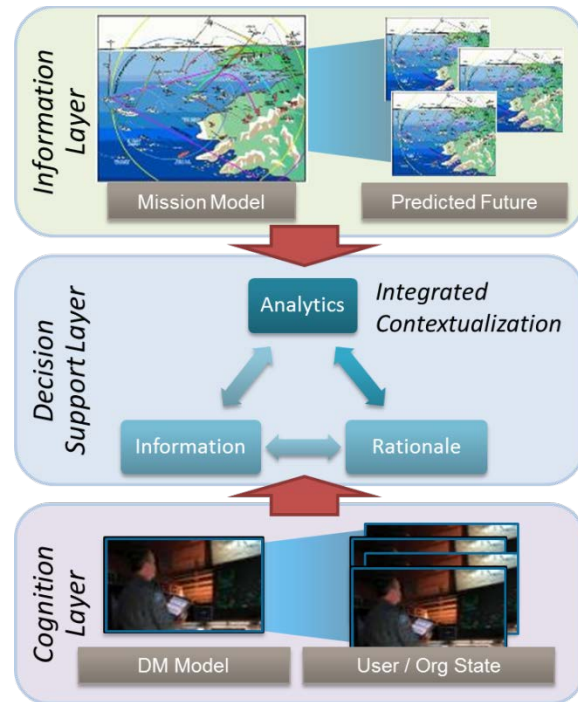


Figure 2-1. 3 Core Layers of InfoCog

InfoCog will improve the decision-making process by predicting context-dependent future information and cognition needs, and use those predictions to deliver tailored information products to optimize mission performance. InfoCog will combine data-centric mission models and prediction algorithms with user-centric representations of immediate and anticipated operator task needs and states, incorporating insights from the data fusion, cognitive science, and systems engineering disciplines. Boston Fusion and Aptima will leverage state-of-the-art techniques from the data fusion and cognitive engineering domains, including Semi-, Hidden, and Partially Observable Markov Decision Processes, Multiple Hypothesis Management, Bayesian Inference, and hybrid Cognitive Task Analysis. These methods will be combined in novel ways to ensure InfoCog's layers perform as expected and deliver information products to operators.

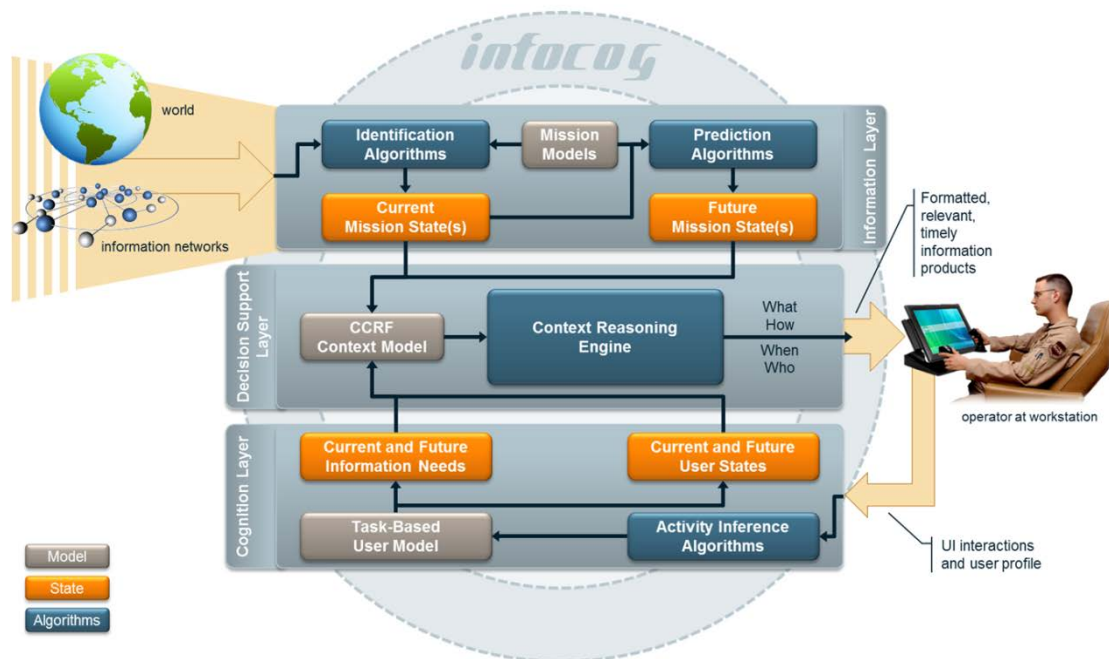


Figure 2-2. InfoCog Functional Architecture

2.2 INFORMATION LAYER

The Information Layer (IL) is responsible for developing the mission context—current estimates and future hypotheses—in the InfoCog system (Figure 2-3). This context comprises the mission state (e.g., which missions are being addressed by the users, and where events are in the mission progression) and the information available to the user to complete the mission. To provide hypotheses of mission context, the IL will monitor relevant C2 data feeds with a focus on both the *type* of information that is being employed, and (to a lesser extent) on the *values* of that information. This “meta” level of observation is well matched to our goal of determining the mission context, in that we are focused on the high-level mission structure and not on the fine-scale details of the mission specifics.

InfoCog will employ these hypotheses of the mission context to recognize significant events and changes in the operational environment that are external to the decision maker. By predicting and hypothesizing future states, IL will support the InfoCog goal of proactive decision support.

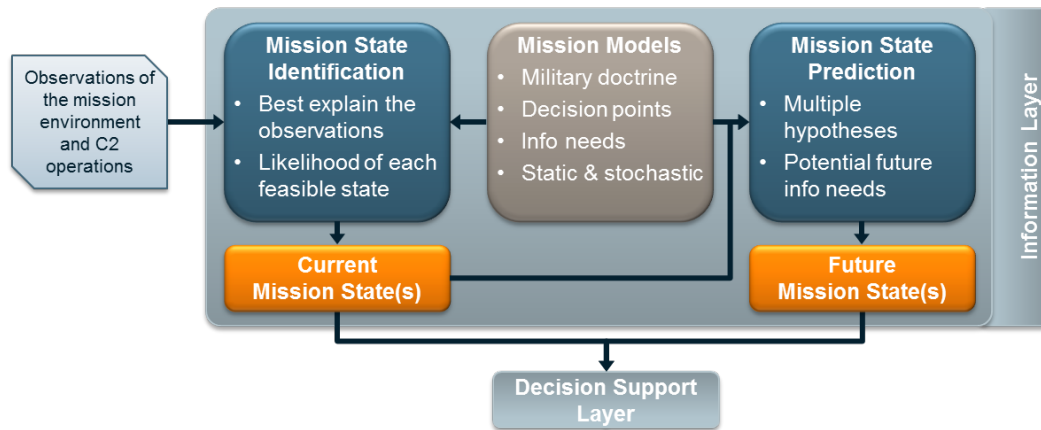


Figure 2-3. Information Layer

Identify Current Mission State

Our team will develop increasingly sophisticated mission state estimation algorithms in a multi-year spiral approach, progressing from doctrine-based deterministic models to more flexible, stochastic models. The IL will initially estimate mission models by fusing parameterized doctrines (defined formal policies and procedures, with identified decision points and information needs) with observations of the actual environment and C2 operations. By observing the type of information being accessed, the suite of tools being employed, and the actions being taken—and fusing the observations with the developed models—IL will calculate the likelihood that the mission is in each of the feasible model(s), estimate the underlying parameters, and dynamically detect when situations diverge from known models.

Note that identifying the mission is not an open-ended problem, and is consequently not intractable. The set of feasible military missions is bounded by the responsibilities of the user's organization. In effect, we will take advantage of the formal policies and procedures inherent to all military operations to define the set of potential missions and mission operations, and select the mission(s) from the set that best explains the observations. That said, even though the suite of missions is defined, “no plan survives contact with the enemy”; hence, we will evolve the IL implementation to include stochastic mission models, specifically the family of Markov decision processes (MDPs; [1]). The simplest MDPs model the mission as a collection of tasks, where the transition from the current task to the next is dependent only on the current task and the action of the user. Semi-Markov decision processes (SMDPs) extend MDPs to include a random “holding time” within each task. Partially-observed Markov decision processes (POMDPs) further generalize MDPs to model aspects such as the stochastic effects of actions, noisy observations, and incomplete information such as knowledge of the current mission task [2]. In each spiral, we will use the deterministic or MDP-family modeling as a formalism to quantify the likelihood of each potential mission state from the (partially) observable data. This identification will take the form of an *a posteriori* distribution over the possible states.

Hypothesize Future Mission State

Given the estimated state of the missions within their models, the IL will then employ these models to predict future mission states and potential trajectories through those future states. Innovative multiple hypothesis management (MHM) techniques will facilitate the prediction capability, creating alternative interpretations of the future state, each scored by its conditional likelihood of occurring [3]. MHM techniques were originally developed for target tracking to efficiently create, maintain, and prune alternative interpretations of the possible data combinations before making a decision on the data, their source, or their accuracy. The implications and data needs of these hypotheses will enable proactive analysis within the decision support layer to anticipate, request, compute, and pre-position information supporting the decision-maker.

2.3 COGNITION LAYER

The Cognition Layer (CL) complements the IL to deliver more relevant and timely information by incorporating user context along with the IL's mission context. As illustrated in Figure 2-4, the CL infers current activity by leveraging observable user interactions and known characteristics of the operator—at login, a user profile is registered containing information about the operator's role, experience, expertise, and preferences. The CL then compares that activity to prescribed task activities, enabling identification and characterization of gaps/mismatches between user actions and expected task activity. These insights are passed to the DSL as current and future user information needs and states. The CL will be developed to combine state-of-the-art techniques for socio-technical system design in a novel fashion: our team will use Hidden Markov Models (HMMs) to infer activities (bottom-up) and a Task-Based User Model (top-down) to compare inferred to expected current activities, and to single out relevant current and future needs and states (e.g., activities, tasks, goals, workload, attention) of the operator.

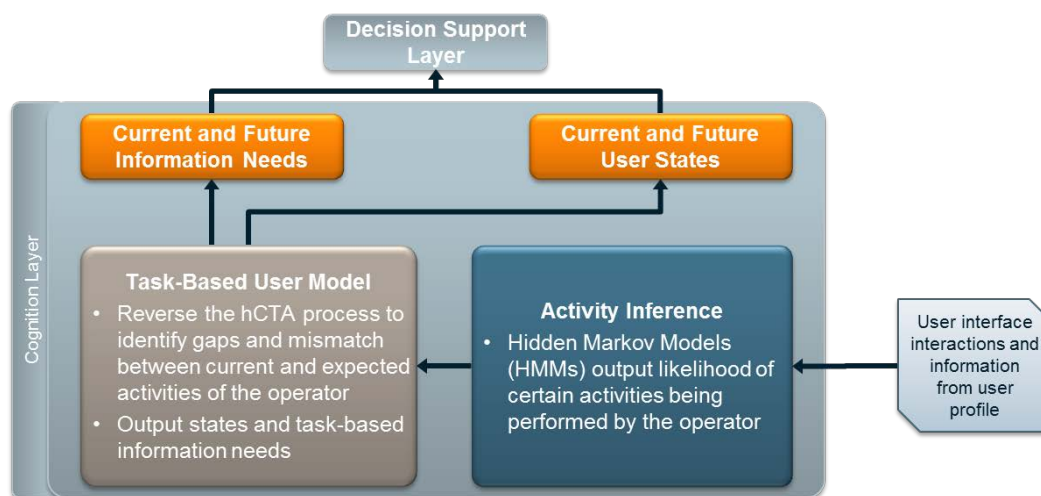


Figure 2-4. Cognition Layer

Activity inference using HMMs

Hidden Markov Models constitute a principal method for modeling partially observed stochastic processes and behaviors – processes that have structure in time [4]. An HMM can sequentially process new information each time an observed transaction occurs. The premise behind HMMs is that the true underlying process (defined as a Markov chain representing the evolution of the data as a function of time) is not directly observable (i.e., is hidden), but it can be probabilistically inferred through another set of stochastic processes, namely observed inferences from data. In relation to the CL, though an operator's mental processes are not directly observable, they can be inferred via system interaction data. Robust task models contribute to greater inference reliability as they provide constraints for interpretation, and violations are quickly recognized (e.g., actions not expected for a task).

Task-based user modeling by reversing the hCTA process

Hybrid Cognitive Task Analysis (hCTA; [5], [6]), is a flexible process, with capabilities beyond existing implementations, designed to derive system requirements for socio-technical systems. Structured around five steps, the hCTA process leads to the generation of key artifacts that describe the user and the system from diverse points of view: a scenario task overview, an event flow diagram, situation awareness requirements, decision ladders, and interface requirements. The hCTA method considers the structure of the environment and of the goals to be achieved, the capabilities and limitations of human operators and automated agents, and the tasks and workflow of the operator to allow the human-machine system to adapt to unanticipated and novel situations.

We propose to employ this process offline to create a baseline Task-Based User Model which specifies expected user activity as described by the hCTA artifacts. We will then reverse-engineer the process online: as activity is inferred by the HMM algorithms, the Task-Based User Model identifies current and impending user tasks, and characterizes possible gaps and mismatches with the baseline. Assessing this mismatch will serve as an initial approximation for user performance and state (e.g., high levels of activity compared to predicted/expected levels, large percentages of time spent in one state versus another, difficulty reaching goals or expected states, etc.). These measures serve as indicators of attention and workload. This hierarchical top down/bottom-up approach is a novel and unique method that will allow for the rapid output of specific, current and future task-based information needs and user states to the DSL.

2.4 DECISION SUPPORT LAYER

To make actionable the insights accumulated in the IL and CL, the Decision Support Layer (DSL) optimizes and maps the available data from the environment (from the IL) to critical needs of the human operator's decision-making space (from the CL). Augmenting decision-making performance requires customized delivery of task-appropriate information. The DSL performs this function by leveraging a context model and a context reasoning engine. As illustrated in Figure 2-5, the DSL uses Aptima's *Common Context Representation Framework*

(CCRF), which structures the data and relationships of the IL and CL so they can be used efficiently by a context-reasoning engine. The context reasoning engine crafts and delivers information products that are tailored for current and upcoming operator needs.

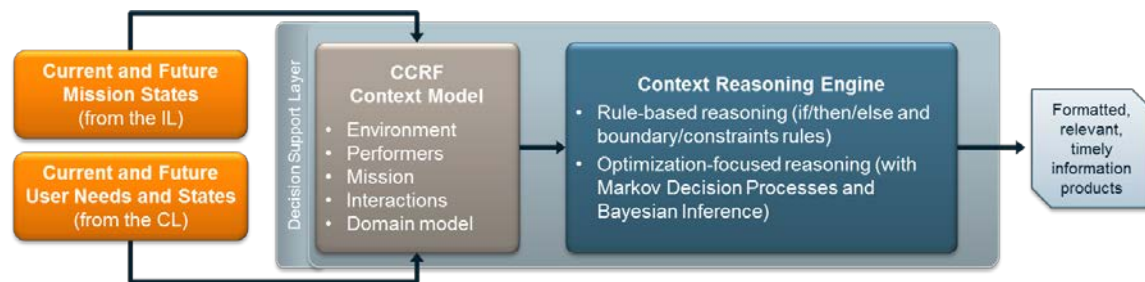


Figure 2-5. Decision Support Layer

The Common Context Representation Framework (CCRF)

To ensure that all relevant data from the IL and CL are efficiently leveraged by the DSL, a common representation of the context elements is needed. This context consists of the tasks themselves, the environment, the goals and capabilities of the operators and systems involved, as well as the interactions between the various elements. CCRF [7] was conceived to provide a framework for representing the types of information needed for synthetic entities to interact and cooperate with human users in the process of pursuing common goals. The CCRF abstraction that frames the context model divides information into five main categories:

1. Environment – A description of the state of the world relevant to the system;
2. Performers – A description of the actors (e.g., human or automation) or users operating within the environment;
3. Mission – A description of goals that indicate a desire to make a change to world state, and the plans and tasks required to achieve them;
4. Interactions – A description of the various communications and actions that can occur between performer and/or resources in the environment; and
5. Domain Model – A description of the domain concepts necessary to bind the abstract concepts mentioned above to a real-world application domain.

The CCRF runtime infrastructure houses all this data in a database and allows CCRF data producers and consumers to access context data programmatically in Java or through a light-weight web-service.

Context Reasoning Engine

The CCRF feeds a Context Reasoning Engine, that determines and distributes mission-relevant information products, formatted and delivered in accord with user needs (computed by the CL). The Context Reasoning Engine enables InfoCog to evaluate, prioritize, and construct an information product with an understanding of how it fits (and will fit), with information already delivered or likely to be delivered in the near future. One of the more critical tasks, the Context

Reasoning Engine is also responsible for balancing information delivery at a pace that does not overwhelm the operator.

The Context Reasoning Engine will be developed at two levels of sophistication in order to mitigate risk and push innovation. In past research efforts [8], Aptima has developed rule-based reasoning engines with straightforward if/then/else and boundary/constraints rules. InfoCog will use such rule-based analyses as an early implementation of the DSL; however the context reasoning will be more advanced after Year 1 and include optimization-based analysis using Partially Observable Markov Decision Processes (POMDPs, particularly well-suited for managing decisions with uncertainty; [9]) and Bayesian Inference (BI). To this end, our team will adapt and apply our partially observable MDPs and BI algorithms, from previous research [10]–[12] where they were developed as means to infer intent and provide goal-oriented and context-relevant automated support in supervisory control.

By structuring the context reasoning engine using MDPs and BI algorithms validated in prior work [13], we will ensure the extensibility of the InfoCog approach beyond the initial scenario and use case scoped in this effort. MDPs and BI algorithms are well suited for this purpose: they are domain-independent and permit reasoning at higher cognitive levels like goals and intent, rather than only tasks and commands (which are domain and mission specific).

3 NARRATIVE

Consider a PACFLT scenario involving the Navy Communications Systems Coordination Center (NCCC), a special-focus support group in PACFLT that gathers, maintains, and shares situation awareness of C4I systems & capabilities within the area of responsibility (AOR)¹. The NCCC Watch Officer and staff work together to provide the Commander with situational awareness on potentially multiple concurrent missions, e.g., anti-piracy, overwatch of potential adversaries, and monitoring regional conflicts. These missions may share operators, timelines and resources, such as sensors, platforms, and networks. Operators continuously monitor mission progress to determine if there are any events of interest occurring, such as piracy activities, change in an adversary's posture, or regional flare ups. These events could trigger additional information collection requirements and analysis. Similarly, loss of a sensor or platform resource—for example due to equipment failure, adversary jamming, or national level retasking—or computer network disruptions due to equipment failure or cyber-attack, can result in incomplete or incorrect situation awareness.

Today's DSSs do not support operators' requirements to detect, understand, and address rapidly these events and their impact across multiple missions. Major current challenges include:

1. Understanding the large volume of data
 - a. Filtering
 - b. Validating
 - c. Correlating
 - d. Processing
2. Identifying the important information contained within the data
3. Detecting missing information
4. Detecting important information changes
5. Acquiring needed information (often manually)
6. Understanding what the information means, especially with respect to the current and future plans and impacts (e.g., 2nd and 3rd order effects)
7. Information is often time-late, unreliable, or potentially compromised – requiring verification and/or validation
8. Selectively prioritizing and focusing on some tasks (often at the expense of others), due to staffing and workload issues

The Information Layer (IL) of InfoCog will continuously monitor the operational environment and compare it to existing mission models, identifying and presenting potential scenario trajectories and information to the operator. Systems and information to be accessed and monitored include:

- Commander's Intent (communicated by or inferred from CCIRs, CIRs, RFIs, SOPs, TTPs, etc.)

¹ Much of the details on NCCC characteristics and operations in this section have been derived from [14].

- DMOC-, N3- and N6-specific CCIRs
- GCCS-M
- C2RPC / MTC2 SOA
- ENMS and other network health status systems
- Message traffic
- Email
- CENTRIXS (multiple versions)
- Websites (SIPR and NIPR sites), internal and external to command
- Internal and web-based documents

InfoCog's models will postulate alternative mission states, identify what information is needed to understand better these potential states, and what resources can support the information collection.

Concurrent to the Information Layer processing operations, the Cognition Layer (CL) of InfoCog is capturing user interactions to infer current and future task needs and user states, and to anticipate how current and likely decision processes need to be supported through information delivery. The Cognition Layer will combine the user interactions with known characteristics (e.g., role, experience, expertise, and preferences) of the operator (NCCC Watch Officer and staff).

Given the IL and CL estimated models, the Decision Support Layer (DSL) will select and format relevant and timely information products that best align with the mission states and operator's related information needs, presenting the most relevant results to the operators in the form they can most easily attend to and understand given their current and anticipated activities, information needs and cognitive states.

InfoCog will automatically fuse and extract important information from a large number of sources (challenges #1, #2, and #4, above) and cross-check them against mission and state models (challenges #6 and #7). InfoCog will support the detection and acquisition of missing information at a faster rate than that of human operators (challenges #3 and #5). Ultimately, InfoCog will allow the NCCC Watch Officer and staff to accelerate decision-making and increase mission readiness and performance through the use of more robust, timely and relevant information (challenge #8).

4 TECHNOLOGY DEVELOPMENT ROADMAP

As shown in Figure 4-1, the InfoCog program is structured around three spirals, where the later part of each phase includes refinement and extension of the core algorithms and components, to define the requirements for the subsequent spiral. This spiral development approach will allow us to incorporate lessons learned from development and evaluation during one spiral into the next, thereby ensuring that we can address those areas that will provide the greatest benefit to the decision support function.

In Year 1, we will focus on developing initial capabilities for the IL and CL, integrated with a nominal DSL. In Year 2, we will place more emphasis on DSL development to create an end-to-end system, as well as perform a demonstration and pilot study with potential end users. In Year 3, we will enhance the baseline functionality to implement fully and integrate additional information and cognitive models, and perform a more complex user study with user data. Finally, in Option Year 4, we will refine and improve the system based on the feedback from the earlier user studies, as well as integrate into the end user system.

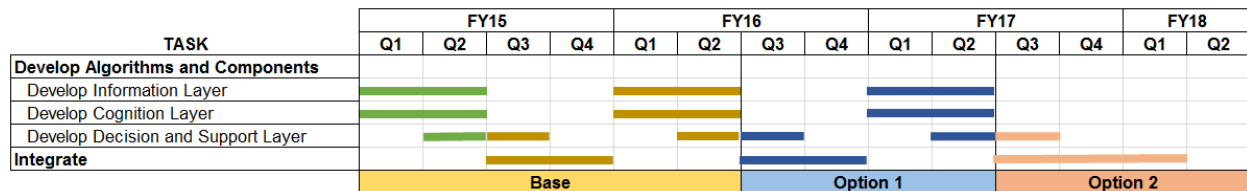


Figure 4-1. InfoCog Schedule

5 RESEARCH REQUIREMENTS

One technology area that we believe could benefit from cross-team research is the general area of *context*. While agreeing on a common definition may not be feasible, it may be possible to identify the common core elements within different approaches, and to identify the information needed (or desired) to develop estimates or models of context. While we are supportive of developing such a common understanding, the InfoCog is not dependent on it and, if necessary, will develop our own approach based on the *Aptima Common Context Representation Framework* (CCRF).

Similar to the area of context is that of developing a common definition for *Commander's Intent* that is amenable to instantiation within a computer processing system. Both context and intent are features of the environment external to PDS that are necessary to understand the mission and what is required. It would be a significant contribution if the overall PDS program can make progress on the definition, structure, and ontology for machine-readable context and commander's intent.

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7 LIST OF SYMBOLS, ABBREVIATIONS, AND ACRONYMS

Abbreviation	Description
AOR	Area of Responsibility
BI	Bayesian Inference
CCIR	Commander's Critical Information Requirement
CCRF	Common Context Representation Framework
CDDM	Context-Driven Decision Making
CENTRIXS	Combined Enterprise Regional Information Exchange System
CIR	Commander's Information Requirement
CL	Cognition Layer
DMOC	Distributed Mission Operations Center
DSL	Decision Support Layer
DSS	Decision Support System
ENMS	Enterprise Network Management System
GCCS-M	Global Command and Control System - Maritime
hCTA	Hybrid Cognitive Task Analysis
HMM	Hidden Markov Model
IL	Information Layer
MDP	Markov decision process
MHM	Multiple hypothesis management
NCCC	Navy Communications Systems Coordination Center
ONR	Office of Naval Research
PACFLT	U.S. Pacific Fleet
PDS	Proactive Decision Support
POMDP	Partially Observable Markov Decision Process
RFI	Request for Information
SMDP	Semi-Markov decision process
SOA	Service-Oriented Architecture
SOP	Standard Operating Procedure
TTP	Tactics, Techniques, and Procedures